PREDICTION OF FORTEAN EVENT REPORTS FROM POPULATION AND EARTHQUAKE NUMBERS

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INTRODUCTION

REPORTS of odd events, generally classified under the vague label of Fortean Phenomena, remain a challenge to science. Are they consequences of: (1) artifacts of human language, (2) the normal memory modifications for odd events (of which most people are not familiar), (3) poor observation, (4) the statistical refuse of otherwise orderly natural principles, (5) routine principles with anisotropic geometries of application, or (6) the sporadic occurrence of phenomena that are symptomatic of other principles not yet measured or understood?

One or more of these solutions have been discussed by various writers with different levels of analytical prowess. The majority of pro- and con-Fortean enthusiasts have used logical arguments or suave semantics in order to demonstrate their point. Since the language used is primarily a nominal scale, composed of 0,1 conditions (something is either true or not true, without intermediate conditions), solutions appear as simple and clear demonstrations.

Unfortunately qualitative conclusions from clever arguments can elicit an illusionary sensation of resolution. One walks away with a simple explanation and with the anxiety of uncertainty removed, only to be frustrated by the next barrage of contradictory and frustrating facts. After a few trials, one begins to suspect the limits of simple language.

Quantitative analyses, whereby numbers rather than words are used, contain almost unlimited degrees of freedom. Whereas with a scale like: true or not true, one would be forced to partial all of the different and unrelated events in the universe into two over-inclusive categories, numerical scales allow the precise (within measurement limits) discrimination of the potentially unlimited events. Using numerical scales, one can seriously predict and understand complex phenomena.

Quantitative analyses require the experimenter to be more than just a verbal acrobat. Clear understanding of methodology becomes more important than mind-blowing metaphors, such as "magnetic windows" or "elastic time." One is faced with a different set of questions that often alters the complexion of the phenomena.

The present study is the first systematic statistical evaluation of Fortean events as a numerical population. Three specific questions were considered as basic themes: (1) How much does population contribute to the numbers of Fortean reports, (2) How much does earthquake history contribute to Fortean reports, and (3) Do different Fortean categories relate in different quantitative ways to these variables?

The first question is critical since human beings are the primary observers (measurement devices) and reporters of odd events. If one can accommodate the majority of the variability in odd-event numbers by population alone, then one is not left with much "numerical room" in which to test various theoretical assumptions. Statements like population contributes a little "or a lot" are not sufficient here. We must know how much of the phenomena is due to population alone.

The second question is a test of a general theory developed earlier.[1] In fact, if one conducts a content analysis of Charles Fort's writing,[2] the semantic connection between earthquakes and odd events is conspicuous. The magnitude of the contribution of earthquake numbers to odd events (if at all) is critical information to test any mechanism involved.

The quantitative solution of the third question is essential for both the methodology and mentality of odd events. If all categories of odd events are predictable in the same manner from known variables and display the same numerical characteristics, then the possibility of any differentiation between possible mechanisms is reduced. As a singular inseparable source of variability, the entire population of Fortean events is reduced to an amorphous mass—smarting significantly of measurement artifact or random error.

The validity of Fortean events cannot be demonstrated with the data sets now available to the researcher. One can only determine reliabilities within limits. In the present analyses, the events, like any probationary phenomena, are considered as *verbal reports*. They should be considered populations of numbers. Neither the acceptance nor the rejection of the phenomena can be based upon a single case or group of cases.

In an area plagued by measurement problems and by the human emotions of theoretical commitment, phenomena can be rejected completely or accepted without question. Some events may be accepted as statistically significant when they are chance, while other events may be rejected as chance when they are reliable. Long and systematic evaluation decreases this likelihood.

METHODS AND RESULTS

Data Sources

A total of 1,153 odd events reported between the years 1850 and 1973 within the 31 states bordering and east of the Mississippi river were used as data. These events were sorted from a larger file of more than 6,000 events that had been the source for *Space-time Transients and Unusual Events*.[1] Approximately 97% of the 385 events reported between 1850 and 1945 were taken directly from the works of Charles Fort.[2] Approximately 98% of the 768 events reported between 1945 and 1974 were collected from *Fate* magazine. The remaining data were collected from various historical publications.

These 31 states were selected since their population

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values have changed systematically over the years with the exception of Florida. States to the west are characterized by longer histories of few human observers and by larger areas. Data from Fort and *Fate* were selected in order to compare the reliability of odd event types. Analyses on two separate populations allow internal checks for: (1) the consistency of any effect isolated and (2) the reliability of classification categories, i.e., whether events recorded as "luminous lights" in the Fort data are similar to the events recorded as "luminous lights" in the *Fate* data.

To reduce sampling or biasing errors, *all* of the events reported (even those with missing values) in the Fort and *Fate* data sources were used. They had been classified and placed on computer cards according to time (hour, day, month, year), space (city/town, state/province, country and continent), category codes, a short verbal description and source. The use of all events reported in the sources reduces exclusion/inclusion artifacts from *ad hoc* or *a priori* conclusions about "which phenomena are real or not real." Obviously, this does not reduce the initial selection bias of either Charles Fort or of the editors of *Fate* magazine.

Since unusual events tend to cluster within one-month periods but display inter-event-intervals of up to several years, simple addition of all events was considered misleading. For example, UFO (unidentified flying object) reports may be reported in several places within a state several times during one week. To obviate this potential artifactual inflation of cases within categories and states, all events from a given category within a state occurring within one month were given no more than a value of 1 (no matter how many redundancies).

Although summary lists for each state were available from information collected for *Space-time Transients and Unusual Events*, a new printout was produced. Events were counted by this experimenter, using the one-month criteria for selection. Only general UFO reports (lights in the sky), feline-like animals and odd glass events (phantoms, snipers, window crosses), displayed any difference from the original data compilation. This difference was minimal. Correlations (for states) between the present and previous analyses were greater than 0.96.

Categories

The data had been coded according to 9 major categories each containing 9 subcategories. The 9 categories were unusual: Falls (FALT), sounds (SOUN), electrical events (ELEC), UFO-related phenomena (UFOT), human occurrences (HUMA), animal sightings (ANIT), "forces" (TELE), geological displays (GEOP), and archeological finds (ARCH). The rationale has been discussed elsewhere.[1]

For this analyses, 4 to 5 or all subcategories of each category were combined. The advantage of this operation is the increased number of events within each category. Many of the subcategories contained 0 or 1 event for more than 25% of the 31 states. Although such nominal data can be accommodated with some statistical methods, a single report (even by a group) is suspect when pattern analyses are involved. Larger sample sizes reduce the anisotropic contribution of an aberrant case to the population, assuming the population approaches some regular function.

The disadvantage of collapsing subcategories involves the arbitrary pooling of possibly different phenomena and mechanisms (even though they had been classified under the same gross category). If the 9 subcategories reflected 9 mutually exclusive mechanisms with different numerical properties, then any unique aspect of each subcategory could be masked. The problem is similar to assuming that all phenomena labeled as UFOs are from a singular source merely because they share the same crude (and over-inclusive) verbal label.[3,4]

The categories or clusters of subcategories used for this analyses (and sample event types for each) were:

FALA: reported falls of rocks, ice, and unusual rains from the sky or inferred falls from immediate proximal observation.

FALB: reported falls of organic materials, including live or dead animals (predominately reptiles/amphibians).

FALT: the combination of FALA and FALB.

ELEC: aurora-like events, mirages of cities and ghost-lights or related events (luminosities occurring in the same area, i.e., 100 m) over at least one decade but not associated with classic haunts.

SOUN: odd sounds: two major sources; first, involving groans, bumps, and related low frequency sounds; second, involving voices with no apparent origins but not related to haunt situations.

UFOA: lights in the sky, including the reports of an odd comet or an odd meteor from Fort's rubric.

UFOB: more complicated and discriminative luminous displays, including phantom, angels, people in the sky and "UFOnauts."

UFOT: the combination of UFOA and UFOB.

HUMA: odd human reports, centered around human loci, such as stigmata, spontaneous human combustion.

ANIA: odd or unusual creatures including feline-like humanoid, reptilian (sea monster) and flying (large birds) types.

ANIB: odd behavior of animals or appearance of known animals such as massive movements, sudden appearances.

ANIT: the combination of ANIA and ANIB.

TELE: odd force-related events, including phantom sniper events, bleeding statues, odd glass etchings following a discrete event (e.g., a storm).

GEOL: unusual geological reports, such as sudden appearance of rocks in fields, large holes (following unknown explosions) in fields, moving rocks, and alleged gravity-magnetic anomalies.

ARCH: unusual, unclassified or noncommensurate (with current theory) archeological findings such as 12 feet tall skeletons, ancient European coins, odd potsherds of "non-existent" cultures. For more details, see (1). All consequent statistical analyses were conducted on a DECSYSTEM 20 computer using SPSS software; sample results were checked manually.

Comparison of Populations

The means and standard errors of the mean (S.E.M.) of each category for the Fort and *Fate* populations are presented in Table 1. For comparison, means and S.E.M.s for the percent contributions of each category to the total number of events for each population are shown as well.

Except for the FALT categories in the Fort data and the ANIT and UFOT categories in the *Fate* data, the percent distribution of the other categories is relatively similar for both populations. In fact, the distortion appears to be primarily a consequence of the heavy loading from the general UFO (UFOA) category in the *Fate* data. If one excludes this category only from both populations of data, the discrepancies are reduced almost to zero except for the FALT and ANIT reports.

The correlation coefficients (Pearson's r) between categories within Fort and *Fate* data are shown in Table 2 while coefficients between Fort and *Fate* populations for the different categories are shown in Table 3. Scattergrams were printed for all correlations and inspected visually for non-linear relationships and extreme values. Since 4 of the states displayed values that were beyond the major cluster, coefficients were calculated for all of the states and 27 states (without the 4 larger values).

TABLE 1

Means ($\overline{X}$) and standard errors of the mean (S.E.M.) for the members of odd events in different categories and for the relative contribution (in percent) of each category to the total population, for both *Fate* and Fort data (n = 31 states).

	Raw Data		*Percent of Total*	
	FORT	*FATE*	FORT	*FATE*
FALA	1.7 ± 0.3	2.2 ± 0.4	18.9 ± 3.9	8.6 ± 1.3
FALB	1.1 ± 0.3	0.5 ± 0.2	9.2 ± 3.0	1.8 ± 1.2
FALT	2.8 ± 0.4	2.7 ± 0.5	28.1 ± 4.5	10.4 ± 1.4
ELEC	0.6 ± 0.1	1.0 ± 0.2	5.1 ± 1.4	4.2 ± 1.0
SOUN	0.3 ± 0.1	0.4 ± 0.1	2.0 ± 0.8	2.0 ± 0.9
UFOA	1.5 ± 0.3	7.9 ± 1.2	10.7 ± 1.6	29.9 ± 2.5
UFOB	0.9 ± 0.2	1.4 ± 0.2	8.5 ± 2.6	7.0 ± 1.2
UFOT	2.4 ± 0.5	9.4 ± 1.3	19.2 ± 2.7	36.9 ± 2.8
HUMA	2.1 ± 0.7	2.1 ± 0.4	14.2 ± 3.4	8.5 ± 1.6
ANIA	0.9 ± 0.2	2.3 ± 0.5	6.0 ± 1.2	9.3 ± 1.6
ANIB	0.3 ± 0.2	4.3 ± 0.7	1.8 ± 1.2	5.2 ± 1.8
ANIT	1.2 ± 0.3	3.6 ± 0.7	7.8 ± 1.3	14.5 ± 2.0
TELE	1.8 ± 0.3	3.4 ± 0.5	13.9 ± 2.3	14.4 ± 2.1
GEOP	0.4 ± 0.1	1.3 ± 0.2	4.2 ± 1.8	5.0 ± 1.0
ARCH	0.7 ± 0.2	0.9 ± 0.2	5.6 ± 1.8	4.1 ± 0.9
ALL	12.4 ± 2.0	24.8 ± 3.5	—	—

The n = 31 and n = 27 analyses were used throughout the study in order to reduce the possible artifacts or distortions from one or two extreme values. Correlation coefficients were calculated for the total population and for the remaining population after extreme (large) values had been deleted following visual inspection of scattergrams. Such operations are important for any analyses since only 1 value that is 10 times greater on both the Y and X values in a random cluster, can produce correlation coefficients of 0.5.

Statistical significance levels are given for different correlation coefficients for the different methods used. Here $p < .01$ is taken as a criterion that the relationship is not a routine chance occurrence. A correlation coefficient that is significant beyond the .01 level would occur by chance alone 1 out of 100 times: or, one would expect that 1 out of every 100 correlation coefficients to be significant by chance alone at this level.

The magnitude of the correlation coefficient required for statistical significance varies with sample size. For 31 cases (states), a correlation value must be 0.46 or greater to be significant at the .01 level. For 27 states, the correlation coefficient must be 0.49 or greater. (Both values assume a two-tailed test considering the nature of the data.)

TABLE 2

Correlation coefficients (r) between categories in the Fort population (above the diagonal) and in the *Fate* population (below the diagonal).

	FALT	ELEC	SOUN	UFOB	HUMA	ANIT	TELE	GEOP	ARCH
FALT	1.00	0.43	0.08	0.45	0.48	0.22	0.45	0.02	0.24
ELEC	0.20	1.00	0.06	0.46	0.30	0.34	0.13	0.21	0.28
SOUN	0.12	0.07	1.00	0.04	0.25	0.14	−0.18	−0.15	0.08
UFOB	0.30	0.22	−0.03	1.00	0.07	0.04	0.09	−0.02	0.19
HUMA	0.50*	0.36	0.19	0.10	1.00	0.59*	0.34	0.14	0.50*
ANIT	0.60*	0.41	0.17	0.30	0.67	1.00	0.54*	0.38	0.54*
TELE	0.60*	0.36	0.09	0.33	0.65*	0.45	1.00	0.12	0.29
GEOP	0.43	0.37	0.43	0.58*	0.40	0.22	0.56	1.00	0.11
ARCH	0.54*	−0.02	−0.05	0.43	0.26	0.25	0.30	0.23	1.00

$r \geq 0.49$, $p \leq 0.1$, two-tailed

One should realize that practical significance and statistical significance are two separate issues. A correlation coefficient that is significant statistically may in actual fact "explain" or account for only a trivial amount of the total variability in the data. For example, a r of 0.50 between variable X and Y appears relatively impressive. However, such a relationship accounts for only 25% ($r^2 = (0.50)^2$) of the variability of the data.

In other words, one can explain or account for only 25% of the variability in X by knowing Y or vice versa. The remaining 75% of the variability in the data is associated with some unspecified source. Even a correlation of 0.90 between X and Y indicates that 20% of the variability cannot be accounted for by the other variable.

Correlations Among Event Categories, Population and Earthquakes

Previous analyses of the data indicated that the three variables: odd events, population and earthquake history of the 31 states were inter-correlated. The relationship between population numbers and event numbers is expected since human beings are the primary measure.[5]

The relationship between population numbers and earthquake numbers is more obscure. However, recent unpublished data indicate a possible explanation for this correlation. States with higher seismic history, within the population analyzed, tend to cluster along the "valley" regions and river basins of the primary mountain ranges and have displayed large areas of fertile regions. Not surprisingly, these areas were settled first and have expanded proportionally.

Based upon previous data, one can offer a probationary explanation for these interrelationships. Whereas population is correlated with event numbers due to the requirement of human observers, earthquakes and populations are interrelated due to a shared third variable: some geological-geographical condition. No doubt the relationship, if any, between odd events and seismic activity will be confounded pervasively by this third variable.

For the present analyses, odd event categories from the Fort data were correlated with population values for the year 1900 (the median value for the Fort printout) and with earthquake numbers between 1700 and 1945 (FQTOT). The *Fate* data were correlated with population values for the year 1960 and for earthquake numbers between 1945 and 1974. The earthquake data were collected from Coffman and von Hake[6] while the population data were taken from U.S. vital statistics.

In order to check the regularity of the correlations between population numbers for different years, correlations were completed between population values for every 10-year interval between 1880 and 1960. All years after 1900 were intercorrelated by more than 0.96. Only 1880 and 1890 showed correlations below 0.90 with the later periods.

Tables 4 and 5 show the correlation coefficients (Pearson's r) between: (1) total numbers of earthquakes and of odd events in different categories and (2) population numbers and odd event numbers, for the *Fate* and Fort data using the total population (n = 31) and the limited population (n = 27). As expected, most of the categories for both populations are correlated significantly with population number. The persistence of these relationships in both n = 31 and n = 27 data indicate these correlations are not due to a few values. This statement is verified by inspection of scattergrams.

TABLE 3

Correlation coefficients (r) for different categories between the Fort and *Fate* data for the different categories and subcategories. Coefficients for all 31 states and without the extreme states (n = 27) are shown.

	n = 31	n = 27
FALA	0.16	0.18
FALB	0.41	0.35
FALT	0.49*	0.46
ELEC	0.57*	0.44
SOUN	0.04	−0.02
UFOA	0.42	0.13
UFOB	0.18	0.00
UFOT	0.36	0.10
HUMA	0.59*	0.42
ANIA	0.22	0.22
ANIB	0.14	0.00
ANIT	0.22	0.16
TELE	0.56*	0.40
GEOP	0.32	0.21
ARCH	0.26	0.27
POP	0.93*	0.72*
QUAKES L	0.56*	0.47
QUAKES H	0.61*	0.57*

$p < .01$

The primary difference between the Fort and *Fate* data is the number of significant correlations between odd events and seismic activity. None of the event categories within the *Fate* data are correlated significantly with the earthquake numbers during that period. On the other hand, depending upon the n = 31 or n = 27 population, several event categories from the Fort data are correlated with the earthquake activity.

If indeed earthquakes are correlated to some or all odd event categories, then some "period-dependence" should be evident. In other words, odd events during a particular interval should be most correlated with earthquake numbers during that period. This statement assumes, of course, that long-term lags—in the order of decades—do not exist between the odd events and quake numbers.

As a check for this possibility, total numbers of earthquakes recorded before 1874, between 1875 and 1909 and between 1910 and 1945 were correlated with the different categories in the Fort data; these three intervals were called QT1874, QT1909 and QT1945, respectively. The greatest changes for the three intervals, respectively, were for FALT (0.46, 0.44, and 0.26), UFOT (0.57, 0.62, and 0.13), HUMA (0.72, 0.36, and 0.02), and ARCH (0.62, 0.46, and 0.28).

The correlation coefficients between the individual intervals displayed a large range. Quake numbers for the

TABLE 4

Correlation coefficients (r) between different event categories and population (in the year 1900) and total earthquake numbers (1700 to 1945) for the data collected from Fort for both n = 31 and n = 27 state analyses.

	n = 31		n = 27	
	P1900	FQTOT	P1900	FQTOT
FALA	0.64*	0.38	0.52*	0.04
FALB	0.39	0.55*	0.44	0.68*
FALT	0.71*	0.61*	0.63*	0.50*
ELEC	0.34	0.42	0.23	0.32
SOUN	0.07	0.17	−0.10	0.09
UFOA	0.56*	0.57*	0.42	0.38
UFOB	0.23	0.53*	0.15	0.47
UFOT	0.51*	0.60*	0.38	0.56*
HUMA	0.70*	0.55*	0.53*	0.48
ANIA	0.74*	0.43	0.48	0.31
ANIB	0.37	0.53*	0.09	0.25
ANIT	0.66*	0.51*	0.39	0.35
TELE	0.64*	0.48*	0.49*	0.31
GEOP	0.28	0.08	0.40	0.03
ARCH	0.54*	0.61*	0.33	0.59*
	P1900:FQTOT = 0.51*		P1900:FQTOT = 0.35	

*$p \leq .01$

QT1874 interval correlated 0.60 with total quake numbers and less than 0.40 with any of the other intervals. The other three intervals correlated between 0.75 and 0.83 with total quake numbers. Correlation coefficients between the low (Mercalli IV and V) and total quakes for the QT1874, QT1909, QT1945, and QT1973 intervals were 0.91, 0.83, 0.94, and 0.98, respectively. On the bases of these data, one would expect little difference between total and IV-V magnitude correlations with odd event categories.

Factor Analysis

The persistent correlation between the different odd-event categories and population, and for that matter, the inter-correlation between categories, suggested that factor analysis was in order. Given an array of correlation coefficients for a set of variables, factor analyses allow the experimenter to determine whether some underlying pattern of relationship exists. If this relationship exists, then the data could be "rearranged" or reduced to a smaller set of *factors*.

Although the single most distinctive characteristic of factor analysis is its data-reduction capability, the isolation of factors allows potential isolation of the *source variables*. Using factor analysis, one can find groups of variables that display shared properties of variability. If completed carefully and systematically, sometimes one can isolate the mechanism associated with the shared source of variability.

Factor analyses involve a large number of different procedures. In this study, the most accepted method: PA 2 is used.[7] All factor loadings were determined from the varimax solution, which gives the clearest resolution (enhances high or low loadings on a factor). Again, since variability is a central operation, separate factor analyses were completed on the n = 31 and n = 27 population for each population of data. Extreme values have been known to grossly distort factor isolations.

The main 9 categories were factor analyzed. Major analyses included: ELEC, FALT, SOUN, UFOT, HUMA, ANIT, TELE, GEOP, ARCH. In most instances, total categories were substituted by one of their major divisions. UFOT was replaced by UFOB, FALT was replaced by FALA and ANIT was replaced by ANIA. These replacements involved the "most strange" of these categories. For a given category (variable) to be significantly loaded upon a factor, a correlation coefficient of greater than 0.4 on that factor was required.

Results of the factor analyses for the Fort and *Fate* data are shown in Table 6. The loading of each variable on the factors are shown in parentheses. Both eigen values and the percent of the total variability of all the categories accommodated by each factor are shown in parentheses beside the factor numbers. Eigen values are measures of relative importance of the factor. (Eigen values of 1.00 or less indicate that the factor explains no more than that explained by a single variable.)

Two to three factors emerged from the n = 31 and n = 27 populations for both the Fort and the *Fate* data. The cumulative variability that can be accommodated by these factors ranged from 64% to 73%. Despite the variable loadings on some factors, some persistent patterns are evident. For example, the variables UFOB, FALT and ELEC appear on the same factors for both *Fate* and Fort data and for both n = 27 and n = 31 analyses. Similarly, some variables, such as TELE, FALT and UFOB are loaded on more than one factor significantly. All four analyses also show the persistence of a cluster composed of FALT, HUMA, ANIT, TELE.

To determine how population and earthquake numbers might load on these factors, FQTOT and P1900 were added to the Fort data while QT1973 and P1960 were added to the *Fate* list. The results were clear and persistent for the Fort data. Whereas the TELE, FALT, HUMA, ANIT cluster was loaded heavily by population (0.72) and lightly by earthquakes (0.41), the factor containing UFOB, FALT and ELEC was loaded heavily by earthquakes (0.70) but not by population (0.38). The third factor was loaded by earthquakes (0.45) but only with the n = 31 analyses. Substitution of QT1909 (1875-1909) did not alter the contribution of the quake variable.

The *Fate* data were different with respect to population and to quake loadings. For these data, population was loaded heavily on Factors 1 (0.70) and 3 (0.40) for both analyses and also on Factor 2 for the n = 27 analyses. Earthquakes during the *Fate* data period were loaded in

a negative way on Factor 3 only for the n = 27 (−.5) and n = 31 (−.60) analyses. The addition of the population and quake data produced a third factor for the n = 31 analyses only. Interestingly, Factor 3 in the *Fate* data contains very high positive loadings of the UFOB and ELEC categories. The addition of UFOA did not alter the factor pattern for either data pools.

To determine whether some of the categories from both the Fort and *Fate* data may fall on the same factors, all major categories of the two data pools were factor analyzed together. The existence of 18 variables rather than 9 variables is expected to inflate the number of factors discriminated. However, with careful interpretation, artifacts can be reduced.

The results of these analyses are shown in Table 7. The six factors that emerged can account for 75% to 78% of the variability. Again, the first factor tended to be weighted by the HUMA, TELE, FALT, and ANIA categories (1s indicate Fort data, 2s indicate *Fate* data). Note that Factor 4 again emerged with ELEC1, UFOB1, and FALT 1.

TABLE 5

Correlation coefficients (r) between different event categories and populations (1960) and total earthquake numbers (1945-1974) for the data collected from *Fate* magazine for both n = 31 and n = 27 state analyses.

	n = 31		n = 27	
	P1960	QT973	P1960	QT973
FALA	0.69*	0.27	0.61*	0.19
FALB	0.44	0.26	0.39	0.17
FALT	0.70*	0.31	0.63*	0.21
ELEC	0.66*	0.01	0.54*	−0.30
SOUN	0.36	0.25	0.38	0.20
UFOA	0.81*	0.11	0.76*	−0.11
UFOB	0.64*	0.02	0.10	0.13
UFOT	0.82*	0.10	0.74*	−0.15
HUMA	0.67*	0.22	0.62*	0.06
ANIA	0.48*	0.10	0.47	0.03
ANIB	0.60*	−0.03	0.48	−0.24
ANIT	0.65*	0.06	0.59*	−0.12
TELE	0.71*	0.28	0.65*	0.11
GEOP	0.59*	0.23	0.59*	0.16
ARCH	0.42	0.14	0.32	0.15
	P1960:QT973 = 0.30		P1960:QT973 = 0.01	

p < .01

The difference between the n = 27 and n = 31 analyses are quite evident as well. The former results show little sharing of categories from both Fort and *Fate* data on the same factors. A given factor is predominated by either 1s (Fort) or 2s (*Fate*). However, the n = 31 analyses show a clear clustering effect whereby both 1s and 2s appear on a single factor such as Factor 1.

As a preliminary identification of these factors, earthquake histories for the Fort and for the *Fate* data and populations for the two periods were added to the analyses. Only the first factor was loaded by population: P1900 (0.83) and P1960 (0.77). Fortean period earthquakes were loaded slightly on Factor 1 (0.44). Factor 4 was loaded by Fortean period earthquakes (0.67) but not by population. Since P1900 and P1960 were so highly intercorrelated, the same analyses were conducted with only one population value (P1900 or P1960); the basic pattern did not change. The clustering of Fortean period quakes on UFOB1, FALT1 and ELEC1 remained persistent.

On the basis of these results, some new variables were computed for further analyses in order to determine the contribution of population and earthquake history (if any) to their occurrence. Categories that appeared on the same factors were computed (added) and given new labels. These computed categories (for Fort and *Fate* separately) were:

PIEZ = (UFOB + FALT + ELEC)
LUMO = (UFOB + ELEC)
MIND = (HUMA + TELE)
EART = (FALA + ELEC + SOUN + GEOP)
FORC = (FALA + TELE)
ODDS = (UFOT + ANIA + ARCH)
EVER = (ALL − UFOA)
ALL = (All 9 total categories)

The inter-correlations for some of these between Fort and *Fate* data are shown in Table 8.

These computations have both positive and negative aspects. One could argue that the different variables (categories) by themselves do not reflect an "integrated" phenomenon, whatever it is, since they are artificial fragmentations due to labeling systems. The computation presents the data as an integrated pool. On the other hand, one could argue that adding similar source data merely amplified any effect artifactually. Such limits should be realized.

Partial Correlation

Inspections of the data demonstrated the association of population numbers, earthquake numbers, odd event numbers, and, implicitly total areas (per state). Partial correlation provides the researcher with a single measure of association describing the relationship between two variables while adjusting for the effects (on variability) from one or more other variables.[7]

Partial correlation can be a helpful tool to unmask spurious correlations. A spurious correlation is defined as a relationship between two variables X and Y in which X's correlation with Y is purely a consequence of X varying with some other variable Z, where Z is the true predictor of Y. If the effects of Z were controlled (partialled out), the X would no longer vary with Y.

To use an example critical of Fortean phenomena in general, assume the relationship between odd events and earthquakes is due to the contribution of population to

odd events. If the contribution of population was held constant, then the correlation between earthquakes and odd events would no longer be statistically significant or as large. In this situation, the original correlation between odd events and earthquakes would be considered *spurious*.

Table 9 shows the first order partial correlation coefficients for the Fort and *Fate* data according to events, population and quake numbers, for different computed categories. The results of using all states (n = 31) and states within the major cluster (as inspected by scattergram) are shown as well. Partials for both Fortean period (QFORT) quakes (1874 to 1945) and *Fate* period (QFATE) quakes (1945 to 1974) are shown to compare populations.

Taking PIEZ1 for example, the partial correlations with population numbers but controlling for quake numbers show a correlation of 0.38 and 0.40 for the n = 27 and the n = 31 data, respectively. The results of correlating PIEZ1 with quakes and controlling for population, on the other hand, produced correlations of 0.49 and 0.55, respectively. One can conclude that the controlling variables for PIEZ1 in this situation would be primarily earthquake numbers during the Fortean period and secondarily population numbers.

PIEZ1, LUMO1, ODDS1, ALLO1 and EVER1, all displayed some correlation with earthquakes even when controlled for population. This was evident to some extent when the data from the Fort period were correlated with earthquakes for the *Fate* period. On the other hand, none of the *Fate* period computed categories were significantly correlated with quakes from either period. Population was the primary control variable.

These data support in general the results of the factor

TABLE 6

Major factors and relative loadings of categories (in parentheses) for n = 31 and n = 27 state analyses for both *Fate* and Fort data.

FORT

n = 27

Factor 1 (3.14, 35%)		Factor 2 (1.44, 16%)		Factor 3 (1.16, 13%)	
FALT	(0.62)	FALT	(0.48)	ANIT	(0.83)
ELEC	(0.67)	ANIT	(0.38)	GEOP	(0.46)
UFOB	(0.71)	TELE	(0.88)		

n = 31

Factor 1 (3.66, 41%)		Factor 2 (1.13, 14%)		Factor 3 (1.04, 12%)	
FALT	(0.48)	FALT	(0.71)	TELE	(0.76)
HUMA	(0.88)	ELEC	(0.59)	ARCH	(0.41)
ANIT	(0.96)	UFOB	(0.42)		
TELE	(0.47)	TELE	(0.42)		
ARCH	(0.42)				

FATE

n = 27

Factor 1 (4.26, 47%)		Factor 2 (1.26, 14%)		Factor 3 (1.04, 12%)	
FALT	(0.44)	FALT	(0.72)	SOUN	(0.40)
ELEC	(0.53)	UFOB	(0.43)	UFOB	(0.40)
UFOB	(0.63)	TELE	(0.40)	TELE	(0.40)
HUMA	(0.72)	ARCH	(0.71)	GEOP	(0.94)
ANIT	(0.78)				
TELE	(0.55)				

n = 31

Factor 1 (4.90, 55%)		Factor 2 (1.22, 14%)	
FALT	(0.61)	FALT	(0.48)
UFOB	(0.69)	ELEC	(0.72)
HUMA	(0.77)	UFOB	(0.65)
TELE	(0.88)	ANIT	(0.71)
GEOP	(0.48)	GEOP	(0.47)
		ARCH	(0.80)

TABLE 7

Major factors and relative loadings of categories (in parentheses) for n = 31 and n = 27 analyses for Fort and *Fate* data combined (n = 18 variables).

n = 27

Factor 1 (5.18, 29%)			Factor 2 (2.49, 13%)			Factor 3 (1.93, 11%)		
ELEC	1	(0.52)	TELE	1	(0.67)	SOUN	1	(−0.48)
TELE	2	(0.51)	HUMA	1	(0.60)	UFOB	2	(0.79)
HUMA	2	(0.74)	ARCH	1	(0.57)	HUMA	1	(−0.49)
FALT	2	(0.65)	ANIT	1	(0.84)	GEOP	2	(0.54)
ANIT	2	(0.92)						

Factor 4 (1.48, 8%)			Factor 5 (1.34, 7%)			Factor 6 (1.21, 7%)		
ELEC	1	(0.75)	ELEC	2	(−0.44)	SOUN	2	(0.69)
UFOB	1	(0.71)	GEOP	1	(−0.50)	GEOP	2	(0.60)
FALT	1	(0.52)	ARCH	2	(0.67)			
			FALT	1	(0.44)			

n = 31

Factor 1 (6.67, 37%)			Factor 2 (2.37, 13%)			Factor 3 (1.43, 8%)		
ELEC	1	(0.60)	ELEC	1	(0.40)	UFOB	2	(−0.43)
ELEC	2	(0.64)	ELEC	2	(0.46)	GEOP	1	(0.70)
UFOB	2	(0.64)	UFOB	2	(−0.44)	ARCH	1	(0.53)
TELE	1	(0.67)	HUMA	1	(−0.64)			
TELE	2	(0.77)	ARCH	2	(0.58)			
FALT	1	(0.70)	ANIT	1	(−0.55)			
FALT	2	(0.73)	ANIT	2	(0.50)			
ANIT	1	(0.72)						
ANIT	2	(0.67)						
HUMA	1	(0.65)						
HUMA	2	(0.72)						
GEOP	2	(0.66)						
ARCH	1	(0.49)						
ARCH	2	(0.53)						

Factor 4 (1.38, 8%)			Factor 5 (1.18, 7%)			Factor 6 (1.12, 6%)		
ELEC	1	(0.46)	UFOB	1	(0.51)	SOUN	2	(0.41)
UFOB	1	(0.52)				UFOB	2	(−0.40)

analyses. Some of the categories of the Fort data are clearly correlated with earthquake and population histories of the states. Other categories are almost totally loaded on the population factor, an observation that suggests a different source for some of the odd events. However, all the categories from the *Fate* data appear to be controlled (predicted) by *only* population data.

The areas of the states are not randomly distributed. Consequently, the possibility exists that some artifact of area could be contributing in a negative or a positive manner to the patterns. Dividing the different event category, population and earthquake numbers by total area of each state, reduces these values to a common unit of area. In addition, this operation introduces a qualitatively different type of relationship: density.

Although a common operation by many scientists, the division by a common factor can be a source of spurious correlation too. If three *uncorrelated* populations of data X1, X2 and X3 are involved and a person divided X1 by X2 to obtain I1 and divided X3 by X2 to obtain I2, then the correlation between I1 and I2 can approach 0.5.[8] By dividing through by a common source, even a random population, the total amount of random distribution is reduced. For populations that are inter-correlated, the solution becomes less determinant, i.e., the division may enhance or cancel the effect.

If completed appropriately, this procedure can enhance the relationship and remove confounding factors that could be masking any effect. Consequently, first order partial correlations were calculated for events/total

TABLE 8

Correlations between Fort and *Fate* data as a function of different data transformations for sample computed categories (following factor analyses), earthquake and population numbers.

	Total Numbers		Events/Area		Events/Population	
Event	n = 31	n = 27	n = 31	n = 27	n = 31	n = 26
PIEZ	0.41	0.23	0.48*	0.39	0.20	0.23
EART	0.48*	0.56*	0.63*	0.23	0.42	0.44
FORC	0.60*	0.44	0.66*	0.63*	0.11	0.30
MIND	0.67*	0.39*	0.79*	0.68*	0.38	0.50*
ODDS	0.44	0.25	0.50*	0.38	−0.11	0.30
ALLO	0.61*	0.41	0.73*	0.53*	0.46*	0.48
QUAKE	0.61*	0.57*	0.71*	0.47	0.69*	0.41
POP	0.93*	0.72*	0.96*	0.94*	—	—

area (of each state) as a function of population/total area and earthquakes/area, and (2) events/population as a function of earthquakes/population and area/population, for each of the computed categories. Except for the significant contribution of seismic activity to the FORC1 (0.58), the basic pattern following division by area did not change from Table 9.

Not surprisingly, the division by population drastically altered the pattern of significant first order partial correlations. Significant partials for quakes (controlling for area/popula-

TABLE 9

First order partial correlation coefficients for sample computed categories for Fort (1s) and *Fate* data (2s) in order to determine the relative contribution of population (1900 for Fort and 1960 for *Fate*) or earthquakes to variability in the categories. For comparison, seismic data for both the Fort (Fort Q) and the *Fate* (*Fate* Q) periods are used for each set of categories.

				n = 27		n = 31	
Variable		NG		Partial r	Partial r	Partial r	Partial r
		With	Controlling for	Fort Q	*Fate* Q	Fort Q	*Fate* Q
PIEZ	1	P	Q	0.38	0.28	0.40	0.49*
PIEZ	1	Q	P	0.49*	0.26	0.55*	0.25
EART	1	P	Q	0.48*	0.60*	0.52*	0.68*
EART	1	Q	P	0.02	0.19	0.21	0.10
FORC	1	Q	P	0.04	0.24	0.21	0.19
FORC	1	P	Q	0.55*	0.67*	0.64*	0.76*
MIND	1	P	Q	0.56*	0.63*	0.68*	0.79*
MIND	1	Q	P	0.16	0.50*	0.26	0.42
ODDS	1	P	Q	0.37	0.41	0.54*	0.66*
ODDS	1	Q	P	0.57*	0.40	0.61*	0.40
ALL	1	P	Q	0.57*	0.67*	0.68*	0.47*
ALL	1	Q	P	0.56*	0.52*	0.63*	0.79*
EVER	1	P	Q	0.60*	0.64*	0.68*	0.81
EVER	1	Q	P	0.59*	0.50*	0.56*	0.50*
PIEZ	2	P	Q	0.80*	0.80*	0.83*	0.85*
PIEZ	2	Q	P	−0.12	−0.23	−0.18	−0.25
EART	2	P	Q	0.79*	0.80*	0.78*	0.76*
EART	2	Q	P	−0.08	0.24	−0.25	0.04
FORC	2	P	Q	0.73*	0.67*	0.78*	0.80*
FORC	2	Q	P	0.25	0.24	0.03	0.16
MIND	2	P	Q	0.69*	0.71*	0.68*	0.72*
MIND	2	Q	P	−0.20	0.15	0.14	0.10
ODDS	2	P	Q	0.76*	0.76*	0.76*	0.81*
ODDS	2	Q	P	0.07	−0.14	0.05	−0.19
ALL	2	P	Q	0.82*	0.60	0.84*	0.85*
ALL	2	Q	P	−0.00	−0.03	−0.09	−0.11
EVER	2	P	Q	0.85*	0.86*	0.82*	0.86*
EVER	2	Q	P	−0.07	0.26	0.00	−0.10

tion) appeared for PIEZ1 (0.75), EART1 (0.58), EVER1 and ALLO1 (0.66) and for FORC2 (0.50) and for ALLO2 and EVER2 (0.62). All other correlations were not significant and predominately negative. Similar patterns held for both n = 31 and n = 27 analyses.

Multiple Regression

Ultimately, we would like to predict the various categories of unusual events from known and measurable variables. Sometimes simple correlations between two variables do not involve all of the necessary variance required to explain or to predict one of the variables. In these instances, one can use multiple regression whereby more than one variable is used to predict a given dependent variable.[7]

Multiple regression allows the calculation of a multiple r value that is the consequence of combining the different variables in the equation. Like the simple r, r^2 is the amount of variability in the dependent variable that can be accommodated by the others. For example, if the r^2 for Y is 0.80 with two variables X and Z in the equation, then $(0.80)^2$ or 64% of the variance in Y can be explained by the combination of X and Z.

The relative contribution of each variable in the equation to the prediction of Y is also calculable. Sometimes all of the major variability can be accounted for by one of the two (or more) variables. Other times, depending upon the phenomenon, each variable may add similar amounts of predictability to the total. Although separately, the two or more variables in the equations may only marginally correlate with Y, together, they may produce substantial multiple correlations.

A primary limit of multiple regression occurs when two or more variables in the equation are themselves highly inter-correlated. "Highly inter-correlated" is an arbitrary term but is usually applied to r values greater than 0.90. In this situation, the high inter-correlation between X and Z themselves, may artifactually inflate the multiple r value for Y.

Using multiple correlation, we can predict how much of the variability in the odd events can be accounted for by the two variables in question: population and seismic activity. If one can obtain multiple rs of 0.90 or greater then one can predict safely that 81% of the variance in the odd events can be predicted by knowing population and earthquake measures. Only 20% of the variability in odd events would be due to some other source/sources. With other data in the social sciences, this variability is related usually to measurement error or scaling "noise."

Table 10 displays multiple rs for sample Fort and sample *Fate* populations. The two most populated single categories: UFOT and HUMA are presented for comparison. As can be seen, the multiple rs range from 0.64 to 0.87 for the Fort data and from 0.67 to 0.87 for the *Fate* data. Translated into predictability, however, one can predict only between 40% to 76% of the variability in different categories as a consequence of knowing population and earthquake history.

The two populations: Fort and *Fate*, differ blatantly with respect to the relative contribution of earthquake numbers and population to the total variability of the categories. In some of the Fort categories, earthquakes contribute, as shown by their r^2 values, most of the explained variance. Population appears trivial. Again, in the *Fate* data, all of the variance is due to population.

TABLE 10

Multiple regression results demonstrating multiple r values and the relative contribution (r^2) of either population or earthquake numbers during the appropriate periods for different categories in the Fort and *Fate* data.

	FORT		*FATE*	
	Fort Q	*Fate* Q	Fort Q	*Fate* Q
PIEZ				
MR	0.80	0.68	0.84	0.83
Q r^2	53%	30%	9%	0%
P r^2	10%	16%	62%	68%
LUMO				
MR	0.60	0.34	0.81	0.80
Q r^2	35%	4%	2%	5%
P r^2	1%	8%	64%	59%
FORC				
MR	0.74	0.73	0.81	0.81
Q r^2	24%	53%	16%	11%
P r^2	30%	0%	51%	56%
UFOT				
MR	0.70	0.56	0.83	0.84
Q r^2	45%	16%	5%	2%
P r^2	4%	15%	68%	68%
HUMA				
MR	0.74	0.70	0.67	0.67
Q r^2	30%	20%	1%	1%
P r^2	24%	32%	45%	45%
EVER				
MR	0.87	0.83	0.86	0.87
Q r^2	51%	26%	0%	0%
P r^2	26%	43%	75%	75%

From the point of view of prediction (even with possible spurious correlations not totally excluded), the multiple regressions completed with events/area as a function of population/area and earthquakes/area show much greater potency. As seen in Table 11, a multiple r of 0.98 is found with the *Fate* data. In other words, 96% of the variability for all basic categories (with the exception of UFOA) when combined can be predicted from population/area and earthquake/area. Whereas population by itself has an r of 0.93 with the EVER category, the earthquakes add an extra 0.05. This is the difference between explaining 86% of the variance and 96% of the variance.

In order to enhance the prediction of the Fort data in particular, since the multiple rs were smaller than the *Fate* categories, various substitutions were made in population and quake variables. Since the Fort data were scattered over a longer period of time than the *Fate* data, one might argue that the use of population for 1900 or the large

TABLE 11

Multiple rs and relative contribution of either population or earthquake numbers for sample computed event categories for both n = 31 and n = 27 analyses. F refers to F-values.

	FORT				*FATE*			
	n = 31		n = 27		n = 31		n = 27	
	rv	F	rv	F	rv	F	rv	F
EVER/A								
MR	0.83	31	0.83	27	0.98	295	0.98	305
Q/A r^2	62%	11	63%	8	9%	56	9%	54
P/A r^2	7%	7	6%	5	86%	112	88%	108
PIEZ/A								
MR	0.78	18	0.77	21	0.95	118	0.96	154
Q/A r^2	57	23	58%	27	13%	34	13%	43
P/A r^2	3%	2	2%	2	76%	198	80%	257
LUMO/A								
MR	0.48	4	0.48	4	0.40	3	0.38	2
Q/A r^2	16%	8	16%	7	6%	2	10%	1
P/A r^2	7%	2	7%	2	10%	5	5%	4
FORC/A								
MR	0.52	5	0.53	5	0.90	60	0.91	57
Q/A r^2	13%	1	13%	1	43%	1	44%	1
P/A r^2	15%	6	15%	5	37%	57	39%	54
MIDWD/A								
MR	0.91	71	0.93	75	0.93	83	0.93	77
Q/A r^2	46%	1	48%	1	8%	15	6%	11
P/A r^2	39%	63	38%	7	78%	33	81%	32

quake interval FQTOT would not display sufficient resolution. However, the use of population figures for the years 1880, 1890, or 1910 did not alter the multiple rs. The specific use of QT1909 also did not alter the prediction potency.

Neither the use of VI or more quakes, quakes of IV or V, total epicenters, or grand total quake numbers enhanced the Fort or *Fate* predictions. In most cases, the multiple rs were less. The use of these values in the *Fate* data reduced the high multiple rs to within the 0.7 to 0.8 range. Reduction of data to events/population as a function of quakes/population and area/population did not allow greater multiple r values.

CONCLUSION AND DISCUSSION

Several repeatable patterns have emerged in the different Fortean event categories analyzed in this study. Simple correlations, partial correlations, factor analyses and multiple regressions all demonstrate the inter-correlation of Fortean phenomena with population. Although all these methods do share similar assumptions of internal operation, the replicable nature of the data patterns increases the general application of the results.

The interrelationship between different odd event categories within either the Fort or *Fate* data as well as between the Fort and *Fate* data are relatively small. Not more than 50% (average 15%) of the variability in any category within the same data pool can be predicted or accounted for by another category in the same pool. Similarly, a given category in the Fort data can account for not more than 50% of the variability in the *Fate* data. The average explained variability between the Fort and *Fate* data was about 20%

Since the population numbers in the Fort data can account for up to 86% of the variability of population numbers in the *Fate* data (or vice versa), one might conclude that the low inter-correlations between odd event categories imply a minimum contribution from population. However, this conclusion is inappropriate for a number of reasons.

First, the variability around the means of each category for each state in the Fort or the *Fate* data is more commensurate for the population data. Whereas the population measures actually involve millions of counts (and

the entire population, statistically speaking), the odd event numbers for each state are only samples. Presumably, all the odd events, by nature of their space-time transient characteristics, have not been counted.

Since the magnitude of the correlation and the amount of variability accounted for by a predictor are a function of the shared patterns of variability, less random variation occurs in the population data due to the sample size. When the population data are correlated with the odd events, the extra sources of random fluctuation from the odd event sampling, decreases the shared variability patterns.

Second, the more complicated analyses all demonstrate that population can account for almost all the variability contributing to the correlations with earthquakes in most categories, especially for the *Fate* data. Since one is more likely to conclude that population numbers are predictors of odd events rather than the odd events are predictors of numbers of people, the population factor appears to account for most of the variability in all odd event categories. Even in categories (within the Fort data) where earthquakes can account for some of the variability, population is still a contributor.

Certainly, one expects population to correlate with the numbers of events since the human being is the primary measurement. It is now clear, for the *Fate* data at least, that the relative sums of all *Fate* events can be accounted for almost entirely by population variability. When converted to events/area and population/area, in fact, almost all the variability in the odd events can be accounted for by population. Without this transformation, more than 75% of the variability is explained.

For the *Fate* data, at least, one can see that population is the control variable. One would be arguing on very precarious ground if explanations of Fortean events were couched in some environmental or theoretical variable. Such a variable would have to almost perfectly match the variability patterns of population to remain hidden.

Statistically, we cannot proceed any further on the population question. The reduction of Fortean phenomena to purely population causes—in a mechanistic sense—does not follow totally although it is implied. At present, we cannot resolve whether the data imply persistent artifacts in the human population or whether odd events are occurring almost homogeneously over that space and the population merely reflects the statistical observation.

The differential contribution of earthquake numbers to the categories within the Fort data strongly suggest that some of the categories may involve different sources of variability (and perhaps mechanism). Specifically, PIEZ and ODDS (and EVER, since it contains these subsets) showed very clear association with the earthquake history of the Fort period.

The association with earthquake numbers is not artifactual to the period, since even the *Fate* quake numbers correlated with the Fortean categories. Any contribution was expected to be lower, (it involves a different time period) but still evident (since Fort and *Fate* period quakes are correlated). In short, one could conclude that the composite of UFOB, FALT, ELEC, and ARCH are influenced by earthquake history.

A more conservative interpretation would be that the earthquake contribution is trivial and perhaps artifactual. Suspiciously, similar categories for both *Fate* and Fort data show similar multiple rs when both quakes and population are in the equation, even though they may contribute to various degrees. One must ask why should the variability explained by quakes in the Fortean data be replaced by a population component in the *Fate* data?

This pattern could be explained as a consequence of just sampling problems. With large samples (and *Fate* contained twice as many cases as Fort data), the errors of sampling are decreased. As one approaches the entire population and the number of cases increase, the discrepancy of sampling error is decreased. One would expect, even *predict,* the obvious. The EVER category *should* show the greatest prediction and correlation with population since it contains the greatest number of samples.

In short, variability in population can account for most of the distribution in the different odd-event categories. No doubt, one could argue that the composite nature of the analyses removed individual cases and potential phenomena. However, the smaller the sample size, especially in this area, the more one is dependent upon the consequences of random variation, error and worst of all: anecdotal reasoning.

At a probabilistic level, one can consider the human being or the entire population of human beings as a series of responses. Statistically, one expects reports of something odd within and throughout the population. Verification attempts, from photographs to multiple reporting by "reliable witnesses," does not alter the mechanisms of statistical occurrence.

The occurrence of these events would be random; their pursual would be comparable to playing dice. Every so often, the enthusiast would "guess" the next number. Although due to chance, the potent reinforcement would maintain the fragments of some theory. With each roll or each event, the theory, by necessity, must become more and more far-fetched. Except for word games, there is no pattern in randomicity.

Although the analyses by spatial (states) increments were confounded by population variables, the isolation of some environmental contributor to Fortean phenomena may still be possible. The use of temporal increments would allow the inclusion of variability associated with dynamic processes. Time lagged correlations for Fortean categories could discriminate any sequential relationships in the data. This procedure has been used successfully with recent UFO reports.[9]

A solution to the Fortean problem, like other dilemmas in the history of science, will require repeated numerical analyses and the generation of specific hypotheses[5] that can be tested with numbers. "Time-pumps," "magnetic windows," and "Supersargasso Seas" are hypnogogic diversions. They do not solve the problem.

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AN APPENDIX TO "THE ONE PHYSICAL EXPERIMENT SCIENCE CANNOT EXPLAIN"

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by T. B. Pawlicki

AMONG the innumerable speculators who have formulated a holographic model to explain universal mechanics, Tom Bearden is best known to me for analyzing the holographic structure mathematically. Our theories are virtually identical except that Bearden has calculated an abrupt, right-angle, *orthorotation* at the point where radiant energy is transformed into a standing-wave vortex; Bearden calculates one orthorotation on each of the three axes of field spin; an orthorotation on one axis transforms radiant energy into the mental signals of words and music; orthorotation on two axes transforms radiant energy into visual, photonic images; the structure of the spherical standing-wave becomes manifest with orthorotation on all three field axes. In contrast, my models demonstrate a gradual rotation of field energy into the standing-wave phase and back to the radiant phases, although radiation is stopped on each of the three axes to bring words, music and mental images into manifestation. It is difficult to gainsay a sound mathematical calculation, but it is perhaps more difficult to deny the validity of constructed models. Paradoxes of this kind usually provoke critics into assuming that one or both theories must be wrong because both cannot be right. But paradoxes of this kind, including the wave/particle dichotomy, arise simply because mutually exclusive mechanics *are* both right. The problem is to perceive the larger perspective in which both views become synthetic instead of contrary. If you take the time to study waves upon the surface of a sizable body of water, you will see a natural physical model demonstrating the mechanics described by both Tom Bearden and myself. As a tent is an involute of a bubble, each wave and wavelet on the surface of water is an involute of the standing-wave vortices in a Plate Flutter Experiment tuned to white sound. The wave always rises at right angles to the veolcity of radiant energy on its proper scale. The rise is always abrupt upon encountering an opposing velocity on the same axis. A wave-front is formed by opposition on two axes; the third axis cannot be observed on a plane surface of water. There is the phenomenon corresponding to Bearden's calculation of *orthorotation*, while the standing-wave phase of the field progresses gradually throughout the full circle or rotation.

(These models have defined the universal hologram almost sufficiently to design an analogue time transport simple enough for home experimenters to construct, like the Vortex Drive prototype.)

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